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Stochastic Joint Inversion Modeling Algorithm of Geothermal Prospects

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ABSTRACT

A stochastic joint inverse algorithm is developed to estimate flow and temperature in the subsurface consistent with available geologic, hydrological, and geophysical data. The approach uses a Markov Chain Monte Carlo global search algorithm. The algorithm starts with an initial geologic model, a set of measured borehole temperatures, and prior estimates of uncertainty or ranges in key physical properties. It can be enhanced through the inclusion of additional geophysical information, such as measured magnetotelluric (MT) or surface resistivity data, and through sensitivity analyses that identify the most meaningful properties or parameters to consider. This model varies during the inversion process through sampling physical properties (permeability; model structure parameters) while using constraints provided by the data (temperature, surface resistivity, and MT). A typical inversion evaluates several thousand possible model configurations in a process that yields a subset that best matches the data. This subset naturally includes reduced posterior uncertainty estimates. The model is tested on a dataset from Superstition Mountain, CA and inversion of an alternate dataset is in progress.

1. INTRODUCTION

The primary goal of geothermal exploration is to find and characterize a site with sufficient heat, water, and hydraulic permeability for commercial exploitation. We have developed a joint inversion algorithm that utilizes multiple geophysical, thermal, and hydrological data sets and to provide results in a quantitative framework. Previous papers (Mellors et al., 2013; 2014; Tompson et al., 2013) have outlined our basic approach. The overall goal is to improve prospect evaluation, which will aid decisions on development and possible future drilling sites. More specifically, we have two main goals: 1) to assess whether a specific model is feasible, and 2) if feasible, what is the likelihood of a significant geothermal resource?

We have performed extensive testing of the algorithm. The approach uses a generalized Markov Chain Monte Carlo (MCMC) inversion process (Mosegaard and Tarantola, 1995), which uses a stochastic approach to compensate for the complexity of geologic systems (Figure 1). The procedure is based on that used in Ramirez et al., (2005; 2011) and uses a staged approach to handle different datasets. This algorithm possesses several advantages: it is flexible, searches the global solution space defined by the stochastic variable distributions, and provides robust uncertainty estimates. The results are expressed as a range of models along with an associated probability density function.

The inversion process begins with a 3-D geologic model that defines the structural geometry and lithology of the prospect as well as associated boundary conditions defining the temperature and water flux. The objective of the inversion is to vary geometry, permeability, porosity, and heat capacity to evaluate whether the data can be matched using a range of reasonable values. If the data can be matched then this serves to validate the model as a possibility and the likelihood of the model is provided. If the data cannot be matched with reasonable values this suggest that the initial a priori model is incorrect. This process is computationally intensive and this paper focuses on the use of sensitivity and reduced order model to reduce computational effort and expand the solution space.

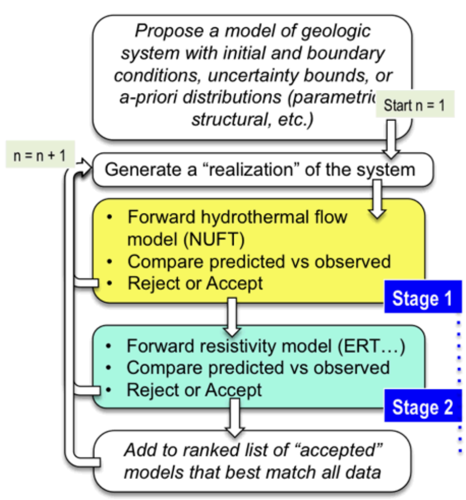

Figure 1: An outline of the stochastic inversion process.

2. METHOD

The framework for the inversion is written in Python but uses different forward codes for each stage. Electrical resistivity is simulated using Multibh, a 3-D finite difference forward modeling code (LaBrecque et al., 1999) and MT forward response is adapted from the Occam 2D forward (e.g. deGroot-Hedlin and Constable, 2004). The model is 3D, and the 3D MT response is approximated by several 2D lines.

In our test case, the basic geologic model was focused on a geothermal prospect near Superstition Mountain, California (e.g., Bjornstad et al., 2006; Tiedeman et al., 2011, Tompson et al, 2008). A geological model was developed and converted to a mesh for the numerical algorithms. It is necessary to use slightly different meshes to accommodate different boundary conditions for each stage such as temperature or resistivity. Fluid and heat flow are modeled using NUFT (Nonisothermal, Unsaturated Flow and Transport), a 3-D multi-phase hydrothermal flow and transport model based upon an integrated finite difference discretization (Nitao, 1998, 2000). Our inversions have usually consisted of running four MCMC iteration loops in parallel, with each set of iterations including approximately 5,000 forward model runs. Most of the computational time is occupied running the fluid/heat flow to equilibrium for each realization. NUFT is parallelized but does not scale well.

The inversion compares the model results with observed data in a staged approach. For example, first the predicted temperature for a well is compared with the calculated values using the MCMC methodology. If the fit between the predicted and observed temperature is satisfactory, then the resistivity (or MT) data is compared. If a model passes all stages, the results are saved. Analysis of the results focuses on the top 10% models that have been saved.

As mentioned above, forward model runs can represent a significant computational burden, despite simplifications that may be adopted for computational parsimony. For example, the current implementation searches a relatively narrow range around the a priori model, in terms of changes in geometry of a hypothesized conjugate fault and the permeability of a transmissive sandstone flow unit. In addition, important parameters and variables and their uncertainties may be difficult to recognize, characterize, or prioritize in advance. Therefore, we seek ways to make the process more efficient and search a wider number of models. Sensitivity Analyses can be conducted beforehand to identify and rank important design variables, as an aid to expert judgment Surrogate or "Lower Order" Models can be developed and trained to efficiently approximate forward model solutions for Sensitivity Analyses and forward simulations in the MCMC loops. We will demonstrate the use of these methods using a test case.

2.1 Test case

The initial test case was based on a geothermal prospect at Superstition Mountain in Southern California, USA. The model used for the inversion is a rectangular cube oriented perpendicular to the strike of the structure (Figure 2). The model extends approximately 6.5 km to the northeast and to a depth of 3.2 km. This area includes temperature profiles obtained in nearby three "NAFEC" wells that differ significantly, with indications of both convection and conduction profiles. Maximum measured temperatures in the wells ranged from 77° to 121°C (171° to 250°F). For the hydrologic model, we assume saturated conditions throughout the entire model depth. We recognize that the actual water table likely lies at a depth between 100 and 120 m (~350 and 400 ft; Dutcher et al., 1972) but including both saturated and unsaturated conditions in the model, while possible, greatly increases the complexity and computational effort. Temperatures are fixed at the top and bottom (27° and 150°C) the top and bottom of the domain and a slight hydraulic gradient is imposed.

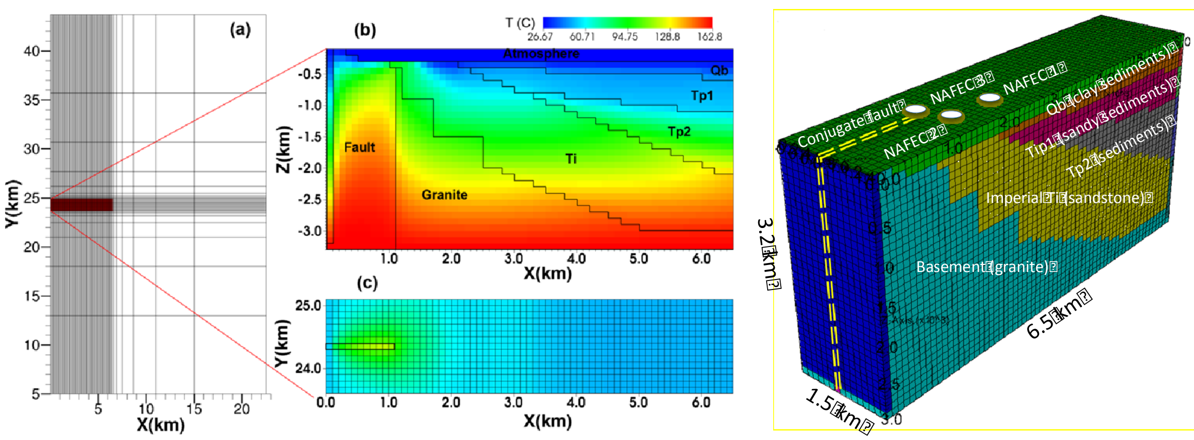

Figure 2: Detailed view of meshing and model used for the test case. The colors in the middle figure correspond to temperature in one model run while colors on the right-hand side distinguish differences in lithology and properties (permeability, thermal conductivity, and resistivity).

Mesh design is challenging for several reasons. The basic mesh was developed using the commercial Earthvision program. However, two additional complexities exist. First, computational effort per trial model should be minimized, as the MCMC process requires thousands of iterations for a suitable solution. Therefore we chose a fairly coarse mesh (100 m in the core of the model). Second, the hydrothermal and resistivity models require different grids, as the resistivity mesh needs to extend into the far-field to avoid excessive edge effects. For a single trial, each grid cell belongs to a specific unit (such as granite) to which model-related properties (e.g., permeability, porosity, and heat capacity) are assigned and drawn from a specific distribution. Note that changes in the geometry of the fault zone are accommodated by re-assigning material "fault" properties to the cells comprising the fault.

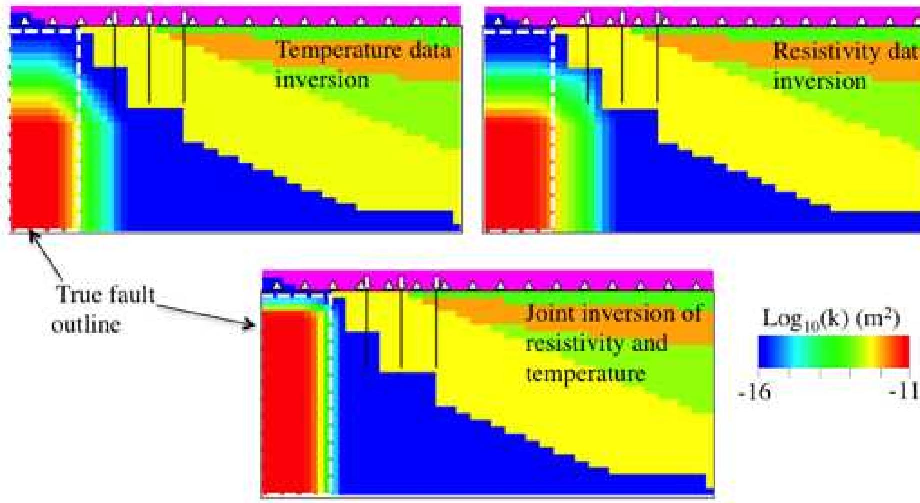

Figure 3: Examples of inversion of a synthetic model using temperature only (top left), DC resistivity only (top right), and both temperature and resistivity (bottom). The joint inversion with both temperature and resistivity matches the original model well. The models are 3D but shown in cross-section.

Initial tests were based on synthetic data. One possible variation of a prospect model was forward modeled to generate synthetic temperature and resistivity data. This synthetic dataset was then inverted. Figure 3 shows the top 10% of the inversion results (mean values), with the possible fault geometries. Note that the joint inversion using both temperature and resistivity yields better results than either technique alone. The inversion was then tested using actual observed data using the temperature gradients measured in the NAFEC wells with good results (Figure 4). In addition to fitting the observed data, a posterior distribution of the input variables is obtained.

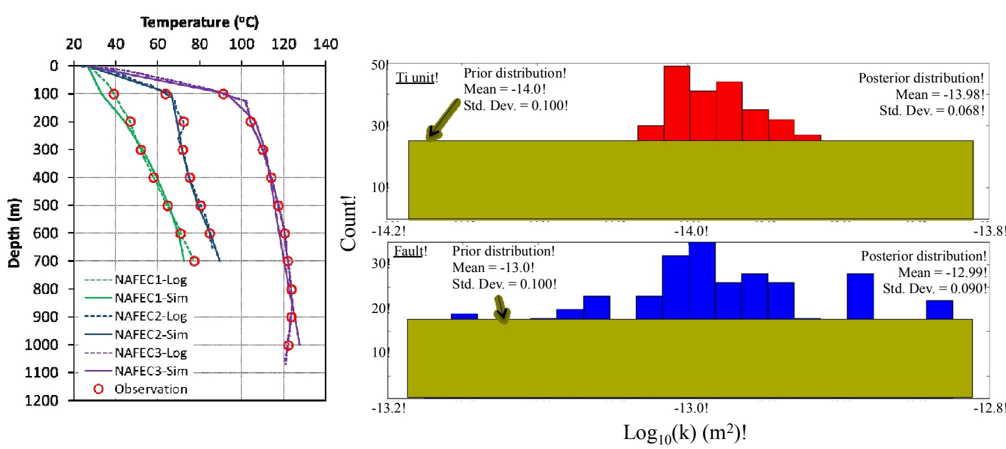

Figure 4: Comparison of inversion results with original model.

However, in this inversion results a 'halo' is observed around the fault. This is caused by the averaging together of a large number of models with different fault sizes that fit the data well. Only when the fault approached the sedimentary units did the model behavior change drastically, as expected. The question immediately arises, how do the results vary as function of each variable? In other words, what is the sensitivity of the model results to variations in each variable? Which variables are the best to consider in an inversion effort?

We begin by focusing on the hydrothermal modeling, as that is the primary computational load. Initially, a "surrogate" model is developed. Surrogate models attempt to approximate the response of a high-fidelity numerical model as a function of a set of key variables. The advantage is that surrogate models are much faster than numerical models, but require some numerical runs to estimate the surrogate parameters. Various methods are available to construct surrogate models, such as polynomials or sparse grid interpolation, but we chose here to use a Multi-variate Adaptive Regressive Spline technique (MARS)(e.g. Chen et al., 2014).

The test case includes 15 key variables of interest. These include permeability and thermal conductivity for five lithologic units (granite and four sedimentary units), as well as the fault permeability, bottom boundary temperature, and the fault height and length. The fault width extends to the boundaries of the 3D model. Note that the log of the permeability is used rather than the actual permeability. To create the surrogate model, 1500 simulations of the model using the NUFT code are run. The model is identical to the one used in the previous stochastic inversion. Each run uses values for the variables drawn from a uniformly distributed distribution defined over a specific range. The desired response values consist of 23 temperature values from the three wells. The MARS algorithm then creates a function that match the 23 temperature values using the 15 key variables. Validation of the MARS model is conducted by omitting one of the 1500 numerical runs as input, estimating the MARS model, and then using the omitted sample to test the MARS model. A full discussion is provided in Chen et al. (2014). Figure 5 compares the results of the predicted temperature in the three wells using the MARS model with the numerical model for both the fitting and the validation stages.

One possible use is to use the MARS model rather than the numerical model in the MCMC inversion to obtain the Bayesian probability estimates. While runs of the full numerical model are required to construct the MARS parameters, the number of runs required (1500) was less than the 5,000 used in the MCMC inversion. Once constructed, the MARS model is much faster than the numerical model. This allows a full MCMC inversion to be conducted in minutes rather than hours or days.

Once the MARS model is constructed, it can be used to estimate the sensitivity of the model to variations in the input variables. Figure 6 shows the 15 input variables ranked in order using Sobol sensitivity indices. Note the geologic units are shown in Figure 2. It is clear that the high permeability associated with the fault is the key driver. This is expected for geothermal systems but it is reassuring that the model is not yielding surprising results. More importantly, it indicates that variations in roughly half of the variables do not have a profound impact on the results, which will simplify future runs of the full inversion.

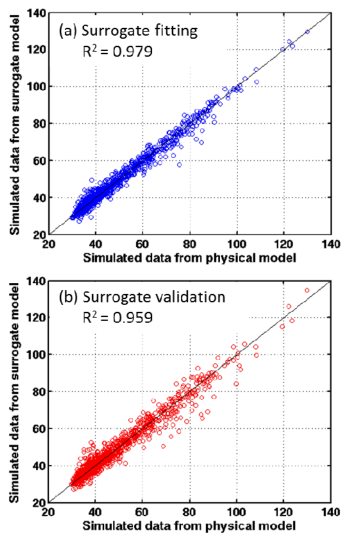

Figure 5: Scatter plots showing mean temperature in the wells for both the MARS and numerical estimates. The upper plot is from the fitting step and the lower plot from validation. From Chen et al. (2014).

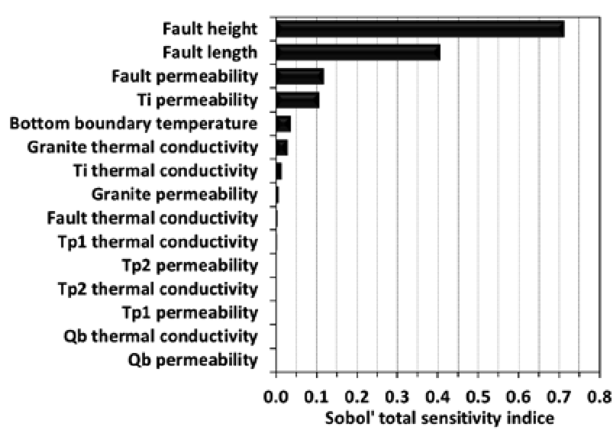

Figure 6: Sensitivity analysis of the key variables. From Chen et al. (2014).

2.2 Alternate test case

We are now testing the inversion scheme on a test case in a different area. One goal is to estimate the time and efforts needed to developed meshes and input parameters for a new area for a finalized version of the code. During the construction of the first case, substantial changes in the Python code were being implemented at the same time, which caused delays. We note that this is a research code and designed for flexibility rather than simple use. Another objective is to test results in an area with wells with known flow rates and temperatures. Currently, we are developing a model for part of the Hawthorne geothermal area (e.g. Meade et al., 2010; Lazaro et al., 2010). In particular, we are focusing on a temperature profile from the HAD-1 well, which show a temperature of 212 degrees F at a depth of 515 feet. This is suggestive of localized out-flow from a nearby source and would be a good test of our modeling capabilities.

The primary difficulties are assembling sufficient geologic and geophysical data to assemble an adequate a priori model. Although the geometry is allowed to vary during the inversion, results are still strongly dependent on the initial model as allowing a large variation in geometries is challenging to adapt in terms of input as well as in terms of computational effort.

3. CONCLUSIONS

We have developed an inversion algorithm and software that works well with temperature and resistivity or MT data. Tests on a test case using data from a geothermal prospect yielded good results but were highly dependent on the initial model. Surrogate 'reduced order' models are good approach to reducing computational effort and yielded substantial reductions in computational efforts. Sensitivity analysis is a key step in running the inversion. A difficulty with the existing code is the time needed to revise inputs with new models.

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